Adaptive and Energy Efficient Wavelet Image Compression For Mobile Multimedia Data Services

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***Abstract* – To enable wireless Internet and other data services using mobile appliances, there is a critical need to support content-rich cellular data communication, including voice, text, image and video. However, mobile communication of multimedia content has several bottlenecks, including limited bandwidth of cellular networks, channel noise, and battery constraints of the appliances. In this paper, we address the energy and bandwidth bottlenecks of image data communication. We present an energy efficient, adaptive data codec for still images that can significantly minimize the energy required for wireless image communication, while meeting bandwidth constraints of the wireless network, the image quality, and latency constraints of the wireless service.**

Based on wavelet image compression, we propose an *energy efficient wavelet image transform algorithm (EEWITA)* for lossy compression of still images, enabling significant reductions in computation as well as communication energy needed, with minimal degradation in image quality. Additionally, we identify wavelet image compression parameters that can be used to effect trade-offs between the energy savings, quality of the image, and required communication bandwidth. We also present a dynamic configuration methodology that selects the optimal set of parameters to minimize energy under network, service, and appliance constraints. We demonstrate the significant energy and air time (service cost) savings possible by using the proposed energy efficient, adaptive image codec under different cellular access technologies.

I. INTRODUCTION

To enable new wireless data services such as mobile multimedia email, mobile Internet access, mobile commerce, mobile data sensing in sensor networks, home and medical monitoring services, and mobile conferencing, there will be a growing demand for content-rich cellular data communication, including voice, text, image and video. One of the major challenges in enabling mobile multimedia data services will be the need to process and wirelessly transmit very large volumes of data. This will impose severe demands on the battery resources of multimedia mobile appliances as well as the bandwidth of the wireless network. While significant improvements in achievable bandwidth are expected with future wireless access technologies, improvements in battery technology will lag the rapidly growing energy requirements of future wireless data services. One approach to mitigate this problem is to reduce the volume of multimedia data transmitted over the wireless channel via data compression techniques. This has motivated active research on multimedia data compression techniques such as JPEG [1,2], JPEG2000 [3,4] and MPEG [5]. These approaches concentrate on achieving higher compression ratio without sacrificing the quality of the image. However, these efforts ignore the energy consumption during compression and RF transmission.

Since images will constitute a large part of future wireless data, we focus in this paper on developing energy efficient and adaptive image compression and communication techniques. Based on a popular image compression algorithm, namely, wavelet image compression, we present an *energy efficient wavelet image transform algorithm (EEWITA)*, consisting of techniques to eliminate computation of certain high-pass coefficients of an image. As shown by our experiments, the use of *EEWITA* can significantly reduce both (i) computation energy, by minimizing the computation needed to compress an image, and (ii) communication energy, consumed by the RF component of the mobile appliance, which is proportional to the number of bits transmitted. The reduction in energy is obtained with minimally perceptible loss in image quality.

We identify several parameters of *EEWITA* that can be varied, and analyze their effects on computation and communication energy, and image quality during wireless image communication. Based on *EEWITA* and its parameters, we have developed an adaptive image codec, which minimizes energy consumption and air time (service cost) needed for an image-based data service, while meeting bandwidth constraints of the wireless network, and the image quality and latency constraints of the wireless service. Central to our proposed adaptive *EEWITA* is a dynamic parameter selection methodology, which can select the optimal *EEWITA* parameters, to minimize energy consumption based on the bandwidth, image quality, and latency constraints. We demonstrate the effectiveness of the energy efficient, adaptive codec by applying it to image communication over multiple wireless access technologies, with significant energy and air time (service cost) savings compared to the use of a statically configured wavelet transform based codec.

The paper is organized as follows. In Section II, we review image compression technique based on wavelet transform for still images, and analyze the computation and communication energy requirements. In Section III, we introduce our *energy efficient wavelet image transform algorithm (EEWITA)*, and analyze and demonstrate its significant potential to save computation and communication energy requirements, with marginal image quality loss. In Section IV, we investigate the effect of other available wavelet image compression parameters on energy consumption and image quality. Section V presents the adaptive *EEWITA*, including a methodology for selecting the optimal image compression parameters which can meet network conditions, service requirements, and appliance constraints. We report on the effects of adaptive *EEWITA* on energy consumption, different cellular access technologies, transmitted pixels per unit energy, and air time (service cost). Section VI concludes the paper.

II. WAVELET IMAGE COMPRESSION

In this section, we first present an overview of image compression. We then describe a typical wavelet transform algorithm, and analyze its energy consumption.

A. Background

Fig. 1 illustrates the main block diagram of the image compression (source coding) process. The image sample goes first through a *transform*, which generates a set of frequency coefficients. The transformed coefficients are then *quantized* (or divided by a certain fixed value) to reduce the volume of encoded data. The output of this step is a stream of integers, each of which corresponds to an index of a particular quantized binary. *Encoding* is the final step, where the stream of quantized data is converted to a sequence of binary symbols in which shorter binary symbols are used to encode integers that occur with relatively high probability. This helps reduce the number of bits transmitted. A number of different encoding schemes are available, such as Huffman coding [6] and run length coding (RLC) [7].

Image compression can be implemented using a variety of algorithms, such as transform-based schemes, vector quantization and subband coding. The selection of an image compression algorithm for multimedia mobile communication depends not

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only on the traditional criteria of achievable compression ratio and the quality of reconstructed images, but also on associated energy consumption and robustness to higher bit error rates.

Recently, the Joint Photographic Expert Group (JPEG [1,2]) has developed a new wavelet-based image compression standard, commonly referred to as JPEG2000 [3,4]. Our preliminary study on wavelet-based image compression (using JPEG2000 [3,4]) shows that the wavelet transform step consumes more than 60 % of the CPU time during image compression process. By optimizing algorithmic features of the transform step, performance and energy requirements of the entire image compression process can be significantly improved. For this reason, we target the wavelet transform step to minimize the energy consumption.

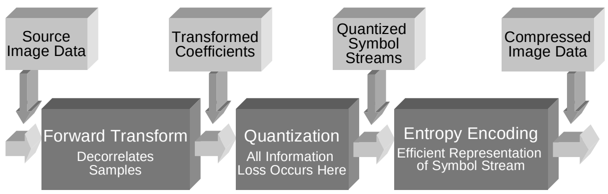
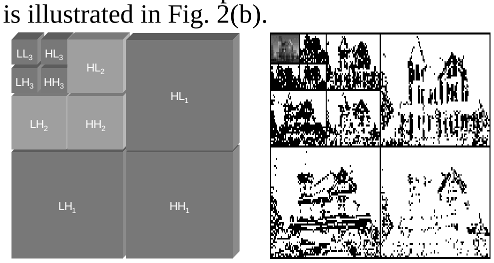


Fig. 1. The image compression process

We next describe a typical wavelet transform algorithm and then go on to analyze its energy consumption.

B. Wavelet Transform Overview

The forward wavelet-based transform uses a 1-D subband decomposition process where a 1-D set of samples is converted into the low-pass subband (L_i) and high-pass subband (H_i). The low-pass subband represents a downsampled low-resolution version of the original image. The high-pass subband represents residual information of the original image, needed for the perfect reconstruction of the original image from the low-pass subband. The 2-D subband decomposition is just an extension of 1-D subband decomposition. The entire process is carried out by executing a 1-D subband decomposition twice, first in one direction (horizontal), then in the orthogonal (vertical) direction. For example, the low-pass subband (L_i) resulting from the horizontal direction is further decomposed in the vertical direction, leading to LL_i and LH_i subbands. Similarly, the high-pass subband (H_i) is further decomposed into HL_i and HH_i. After one level of transform, the image can be further decomposed by applying the 2-D subband decomposition to the existing LL_i subband. This iterative process results in multiple "transform levels". For example, in Fig. 2(a), the first level of transform results in LH_1, HL_1, and HH_1, in addition to LL_1, which is further decomposed into LH_2, HL_2, HH_2, LL_2 at the second level, and the information of LL_2 is used for the third level transform. We refer to the subband LL_i as a low-resolution subband and high-pass subbands LH_i, HL_i, HH_i as horizontal, vertical, and diagonal subband respectively since they represent the horizontal, vertical, and diagonal residual information of the original image. An example of three-level decomposition into subbands of the image *CASTLE* is illustrated in Fig. 2(b).



(a) (b)

Fig. 2. (a) The process of 2-D wavelet transform applied through three transform levels
(b) Demonstration using image *CASTLE*

Having described the operation of the wavelet transform algorithm, we now address its efficiency from an energy standpoint.

C. Analysis of Energy Consumption

We choose the Daubechies 5-tap/3-tap filter [8] for embedding in the forward wavelet transform. The main property of the wavelet filter is that it includes neighborhood information in the final result, thus avoiding the block effect of DCT transform [9]. It also has good localization and symmetric properties, which allow for simple edge treatment, high-speed computation, and high quality compressed image. In addition, this filter is amenable to energy efficient hardware implementation because it consists of binary shifter and integer adder units rather than multiplier/divider units. The following equation represents the Daubechies 5-tap/3-tap filter.

$$L[2n] = \left\lfloor \frac{-x[2n-2] + 2x[2n-1] + 6x[2n] + 2x[2n+1] - x[2n+2] + 2}{4} \right\rfloor$$

$$H[2n+1] = \left\lfloor \frac{-x[2n] + 2x[2n+1] - x[2n+2]}{2} \right\rfloor$$

To determine the energy efficiency of each algorithm, we use a metric that is independent of the detailed implementation of the algorithm. We analyze energy efficiency by determining the number of times certain basic operations are performed for a given input, which in turn determines the amount of switching activity, and hence the energy consumption. For example, in the forward wavelet decomposition using the above filter, 8 shift and 8 add operations are required to convert the sample image pixel into a low-pass coefficient. Similarly, high-pass decomposition requires 2 shift and 4 adds. We model the energy consumption of the low/high-pass decomposition by counting the number of operations and denote this as the *computational load*. Thus 8S + 8A units of computational load are required in a unit pixel of the low-pass decomposition and 2S + 4A units for the high-passes.

For a given input image size of M × N and wavelet decomposition applied through L transform levels, we can estimate the total computational load as follows. Suppose we first apply the decomposition in the horizontal direction. Since all even-positioned image pixels are decomposed into the low-pass coefficients and odd-positioned image pixels are decomposed into the high-pass coefficients, the total computational load involved in horizontal decomposition is 1/2MN(10S+12A). The amount of computational load in the vertical decomposition is identical. Using the fact that the image size decreases by a factor of 4 in each transform level, the total computational load can be represented as follows:

Computational load :

$$C_{AWIC} = MN(12A+10S)\sum_{l=1}^{L}\frac{1}{4^{l-1}} = MN(12A+10S)\frac{1-4^{-L}}{1-4^{-1}} \le \frac{4}{3}MN(12A+10S)$$

Besides various arithmetic operations, the transform step involves a large number of memory accesses. Since the energy consumed in external and internal data transfers can be significant, we estimate the *data-access load* by counting the total number of memory accesses during the wavelet transform. At a transform level, each pixel is read twice and written twice. Hence, with the same condition as the above estimation method, the total data-access load is given by the number of read and write operations:

Data-access load :

$$C_{READ\_AWIC} = C_{WRITE\_AWIC} = 2MN\sum_{l=1}^{L}\frac{1}{4^{l-1}} \le \frac{8}{3}MN$$

The overall *computation energy* is computed as a weighted sum of the computational load and data-access load. From our implementation experiments, we found that the add operation requires two times more energy consumption than the shift operation, and the energy cost of the *data-access load* is 2.7 times more than the *computational load*. We also estimate the *communication energy* by C*R, where C is the size of the compressed image (in bits) and R is the per bit transmission energy consumed by the RF transmitter.

Having analyzed the sources and magnitude of energy consumption in the wavelet transform, we next present techniques to minimize the computation energy as well as communication energy needed in wavelet-based image compression and wireless transmission.

III. Energy Efficient Wavelet Image Transform Algorithm (EEWITA)

In this section, we present *EEWITA*, a wavelet-based transform algorithm that aims at minimizing computation energy (by reducing the number of arithmetic operations and memory accesses) and communication energy (by reducing the number of transmitted bits). Further, the algorithm aims at effecting energy savings while minimally impacting the quality of the image.

EEWITA exploits the numerical distribution of the high-pass coefficients to judiciously eliminate a large number of samples from consideration in the image compression process. Fig. 3 illustrates the distribution of high-pass coefficients after applying a 2 level wavelet transform to the 512 × 512 Lena image sample [10]. We observe that the high-pass coefficients are generally represented by small integer values. For example, 80 % of the high-pass coefficients for level 1 are less than 5. Because of the numerical distribution of the high-pass coefficients and the effect of the quantization step on small valued coefficients, we can estimate the high-pass coefficients to be zeros (and hence avoid computing them) and incur minimal image quality loss. This approach has two main advantages. First, because the high-pass coefficients do not have to be computed, *EEWITA* helps to reduce the *computation energy* consumed during the wavelet image compression process by reducing the number of executed operations. Second, because the encoder and decoder are aware of the estimation technique, no information needs to be transmitted across the wireless channel, thereby reducing the *communication energy* required.

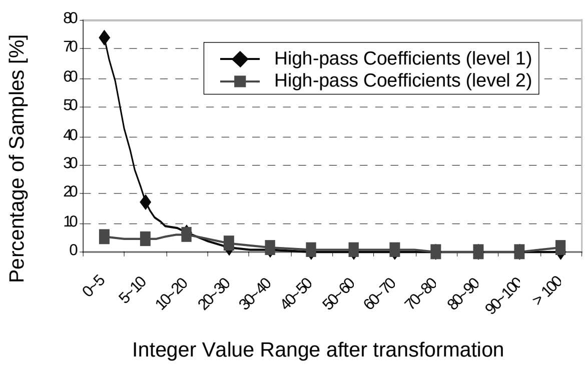


Fig. 3. Numerical distribution of high-pass coefficients after wavelet transform through level 2

Using the estimation technique presented, we have developed our *EEWITA* which consists of two techniques attempting to conserve energy by avoiding the computation and communication of high-pass coefficients: The first technique attempts to conserve energy by eliminating the least significant subband. Among the four subbands, we find that the diagonal subband (HH_i) is least significant (Fig. 2), making it the best candidate for elimination during the wavelet transform step. We call this technique "*HH elimination*". In the second scheme, only the most significant subband (low-resolution information, LL_i) is kept and all high-pass subbands (LH_i, HL_i, and HH_i) are removed. We call this "*H* elimination*", because all high-pass subbands are eliminated in the transform step.

We next present details of the HH and H* elimination techniques, and compare the energy efficiency of these techniques with the original AWIC algorithm which refers to the wavelet transform algorithm without elimination as described in Section II-B,C.

A. Energy Efficiency of Elimination Techniques

To implement the HH and H* elimination techniques (*EEWITA*), we modified the wavelet transform step as shown in Fig. 4. As explained in Section II-B, during the wavelet transform, each input image goes through the row and column transform decomposing the image into four subbands (LL, LH, HL, HH). However, to implement the HH elimination technique, after the row transform, the high-pass coefficients are only fed into the low-pass filter, and not the high-pass filter in the following column transform step (denoted by the lightly shaded areas in Fig. 4 under <HH Elimination>). This avoids the generation of a diagonal subband (HH). To implement the H* elimination technique, the input image is processed through only the low-pass filter during both the row and column transform steps (shown by the lightly shaded areas under <H* Elimination>). We can therefore remove all high-pass decomposition steps during the transform by using the H* elimination technique.

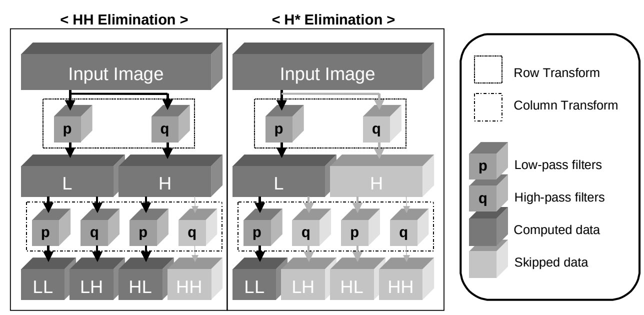


Fig. 4. Data flow of the wavelet transform step with HH/H* elimination techniques (*EEWITA*)

To estimate the energy efficiency of the elimination techniques (*EEWITA*) presented, we measure the computational and data-access loads using the same method outlined in Section II-C. We assume the elimination techniques are applied to the first E transform levels out of the L total transform levels. This is because the advantage of eliminating high-pass coefficients is more significant at lower transform levels.

In the HH elimination technique, the computation load during the row transform is the same as with the AWIC algorithm. However, during the column transform of the high-pass subband resulting from the previous row transform, the high-pass subband (HH) is not computed. The results in Section II-C show that this leads to a savings of 1/4MN(4A+2S) operation units of computational load (7.4 % compared to the AWIC algorithm). Therefore, the total computational load when using HH elimination is represented as:

Computational load :

$$C_{HH} = \frac{MN(22A+19S)}{2}\sum_{l=1}^{E}\frac{1}{4^{l-1}} + MN(12A+10S)\sum_{l=E+1}^{L}\frac{1}{4^{l-1}}$$

Because the high-pass subband resulting from the row transform is still required to compute the HL subband during the column transform, we cannot save on "read" accesses using the HH elimination technique. However, we can save on a quarter of "write" operations (12.5 % savings) during the column transform since the results of HH subband are pre-assigned to zeros before the transform is computed. Thus, the total data-access load is given by:

Data-access load :

$$C_{READ\_HH} = C_{READ\_AWIC}, \quad C_{WRITE\_HH} = \frac{7}{4}MN\sum_{l=1}^{E}\frac{1}{4^{l-1}} + 2MN\sum_{l=E+1}^{L}\frac{1}{4^{l-1}}$$

The HH elimination technique also results in significant communication energy savings. For each transform level that the HH elimination technique is applied, 25 % of the image data is removed leading to less information to be transmitted over the wireless channel.

While the HH elimination technique reduces some computation loads during the transform steps by eliminating one out of every four subbands, the H* elimination technique targets more significant computation energy savings. In the H* elimination technique (Fig. 4), only the LL subband is generated and all high-pass subbands are removed. Thus, only even-positioned pixels are processed in the row transform and fed to the subsequent column transform. Odd-positioned pixels are skipped, since these pixels represent all the high-pass coefficients (HL, HH). Similarly, at the column transform step, all odd-columned pixels are skipped and only even-columned low-passed pixels are processed. This leads to a savings of MN(6A+4S) operation units of computational load (over 47 % compared to the AWIC algorithm). Therefore, the total computational load when using H* elimination is represented as:

Computational load :

$$C_{H^*} = 6MN(A+S)\sum_{l=1}^{E}\frac{1}{4^{l-1}} + MN(12A+10S)\sum_{l=E+1}^{L}\frac{1}{4^{l-1}}$$

H* elimination also reduces the data-access load significantly. Since the wavelet transform utilizes neighborhood pixels to generate coefficients, all image pixels should be read once to generate low-pass coefficients in the row transform. However, in the column transform, only even-columned pixels are required. We therefore can reduce the number of "read" accesses by 25 %. Similarly, since only low-pass coefficients (L, LL) are written to memory and accessed through the next transform steps, write operations are saved by 63 %. The total data-access load is given by:

Data-access load :

$$C_{READ\_H^*} = \frac{3}{2}\sum_{l=1}^{E}\frac{MN}{4^{l-1}} + \sum_{l=E+1}^{L}\frac{2MN}{4^{l-1}} \quad C_{WRITE\_H^*} = \frac{3}{4}\sum_{l=1}^{E}\frac{MN}{4^{l-1}} + \sum_{l=E+1}^{L}\frac{2MN}{4^{l-1}}$$

The H* elimination technique can result in significant savings in communication energy since three out of four subbands are removed from the compressed results. The extent of savings in computation and communication energy using these techniques will be demonstrated in the next section.

B. Experimental Results

In this section, we report on experiments conducted to evaluate the energy savings made possible by using the proposed elimination techniques. In particular, we report on the savings in computation and communication energy using the elimination techniques, and discuss their impact on image quality.

1) Effects on Computation Energy and Image Quality

In the first experiment, we report on computation energy consumed and the image quality generated by each of the two elimination techniques as described in the previous section, and compare the results with the AWIC algorithm. In our experiments, we used the Lena image sample [10], and measured the computation energy and the PSNR of the compressed image, for each of the two techniques, under different levels of elimination. We embed the Adaptive Wavelet Image Compression (AWIC) algorithm developed under the MITRE-Sponsored Research Program [11] to extract the compressed bit size and image quality. In each case, the quantization level was set to 64, and Huffman encoded.

The results are presented in Fig. 5. The x-axis represents increasing levels of elimination, while the y-axes represent computation energy (computed as a function of computational and data-access loads), normalized to that of the AWIC algorithm (without elimination), and the difference of the PSNR with that obtained using the AWIC algorithm. Bold lines represent savings in computation energy using the HH and H* elimination techniques. Dashed lines represent the difference in image quality obtained by using the HH and H* elimination techniques.

From Fig. 5, we observe that the H* elimination technique leads to significant energy savings over the AWIC algorithm, sometimes at nominal loss in image quality. For example, at elimination level 1, the energy savings using H* elimination is about 34 %, while the loss in image quality is negligible. At elimination level 2, the H* elimination technique yields 42 % energy savings, while the image quality degradation is within 3dB. Fig. 5 also shows that significantly more energy savings can be accomplished using H* elimination over HH elimination. However, the degradation in image quality is more significant in the case of H* elimination.

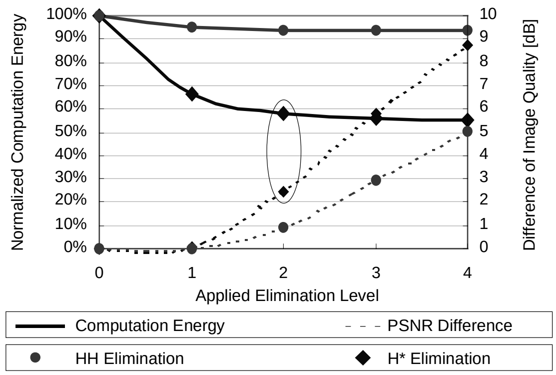
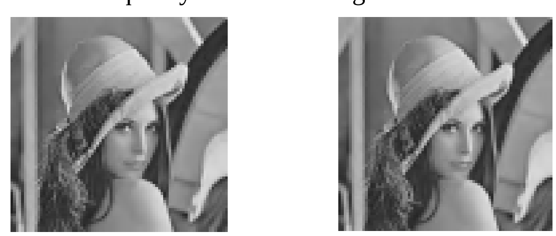


Fig. 5. Effects of elimination techniques on image quality and computation energy

To get an idea of the impact on image quality, we next present visual comparisons of two versions of the Lena image obtained. The image shown in Fig. 6(a) is obtained by using the AWIC algorithm, while the image shown in Fig. 6(b) is obtained using the H* elimination technique through level 2. The PSNRs of the two images are 31.08 dB (AWIC) and 28.63 dB (H* level 2) respectively. Note that while the energy saving between the two approaches is significant (42 %), there is almost no perceivable difference in the quality of the two images.



(a) AWIC : PSNR = 31.08dB

(b) H* Elim. (through level 2) : PSNR = 28.63dB

Fig. 6. Comparison of image quality after AWIC and H* elimination techniques using the Lena 512×512 grayscale image sample.

2) Effects on Communication Energy and Image Quality

In the next experiment, we report on the image quality obtained, and the communication energy consumed in transmitting the compressed image, using the HH and H* elimination techniques. The experimental set up is the same as in Section 1). The communication energy for each technique is estimated from the size of the compressed image.

In Fig. 7, bold lines represent the communication energy savings obtained using the HH and H* elimination techniques, as normalized to the AWIC algorithm. The dashed lines represent the degradation in image quality compared to the AWIC algorithm under different levels of elimination using the HH and

H* elimination techniques. From Fig. 7, we note that when the H* elimination technique is applied through level 2, the communication energy consumption is 37 % less compared to the AWIC algorithm, while the image quality degradation is within only 3 dB. As the number of elimination levels increase, the savings in communication energy increases. However, in doing so, the quality of image also degrades, demonstrating a trade-off between communication energy and quality of image obtained.

The above experiments demonstrate that depending on the image quality desired by a wireless service, and the state of the battery of the wireless appliances, by applying the HH and H* techniques at different levels of elimination, different trade-offs can be obtained between the image quality obtained and the energy expended in compressing the image and transmitting the compressed image.

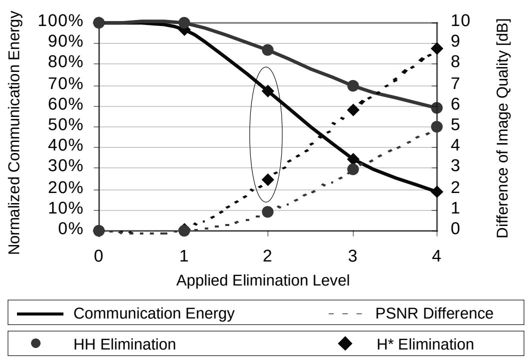


Fig. 7. Effects of elimination techniques on image quality and communication energy

IV. Wavelet Image Compression Parameters

Besides the elimination techniques we have introduced, there are other wavelet image compression parameters, which can be used to minimize computation and communication energy consumed, and effect the desired trade-off between energy consumed, image quality obtained, and bandwidth and air time (service cost) expended during multimedia mobile communication.

A. Varying Wavelet Transform Level

As mentioned in Section II-B, increasing the applied wavelet transform level can reduce the number of transmitted bits, leading to less communication energy for mobile image communication. However, increasing the transform level also results in an increase in computation energy consumption.

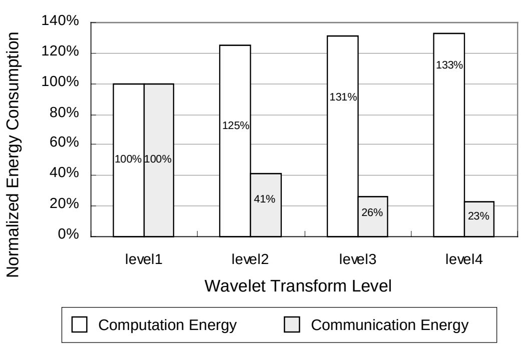


Fig. 8. Effects of varying wavelet transform level on energy consumption (computation and communication energy)

In Fig. 8, the effect of four different transform levels on computation and communication energy is presented. The figure illustrates the increase in computation energy and the decrease in communication energy as the transform level increases for a constant quantization level (30). Note that when the handheld is transmitting data, communication energy will dominate computation energy, and a higher transform level may bring significant overall energy savings.

B. Varying Quantization Level

The goal of quantization is to reduce the entropy of the transformed coefficients so that the entropy-coder can meet a target bit-rate, which is lower than the required bit-rate for wireless transmission. Varying the quantization level of the wavelet image compression algorithm has several effects on mobile image communication. By increasing the quantization level, we can decrease the number of transmitted bits, leading to a lower bit-rate and less communication energy, latency, and bandwidth required to wirelessly transmit the image. However, increasing the quantization level has negative effects such as decreasing the image quality. Fig. 9 illustrates these trade-offs: increasing the quantization level (x-axis) leads to less communication energy, but decreases the quality of image (PSNR) (y-axes).

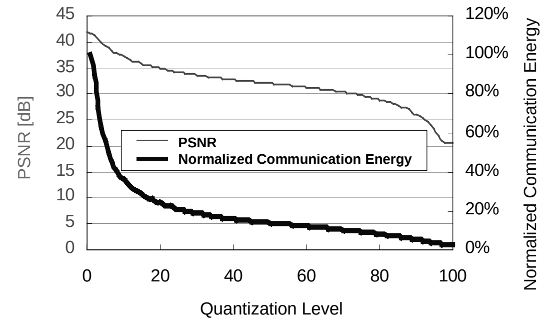


Fig. 9. Effects of varying quantization level on image quality and communication energy

V. Adaptive Image Communication

As demonstrated in Sections III and IV, varying the three parameters (wavelet transform level, elimination level, and quantization level) of the new energy efficient image compression algorithm, *EEWITA*, can produce significant impact on the computation and communication energy needed, and the image quality obtained, in wireless image communication. Based on *EEWITA* and its parameters, we have developed an adaptive image codec, which can minimize energy consumption and air time (service cost) needed for an image-based wireless service, while meeting bandwidth constraints of the wireless network, the image quality, and latency constraints of the wireless service. Central to the adaptive *EEWITA* is a dynamic parameter selection methodology, which can select the optimal Transform Level (TL), Elimination Level (EL), and Quantization Level (QL), to minimize energy consumption based on the bandwidth, image quality, and latency constraints. We first describe a low-cost dynamic parameter selection methodology. We next demonstrate the effectiveness of the energy efficient, adaptive codec by applying it to image communication over multiple wireless access technologies.

A. Dynamic Parameter Selection Methodology

Our dynamic parameter selection methodology, shown in Fig. 10, consists of three steps, two of which are performed off-line, with the third step performed on-line (in a mobile or basestation unit). The first step pre-computes image quality (PSNR) and compression ratio (bits per pixel) for each possible combination of the *EEWITA* parameters (TL, EL, QL) using several image samples. In the second step, we average the results of the first step and sort them for each possible image quality (PSNR) and compression ratio (CR) combination, and store them in a lookup table. In the third step, given the network, service, and appliance constraints such as bandwidth, transmission latency, image quality, and appliance battery condition (energy constraint), the required PSNR and CR are first computed. Next, a table lookup is performed to identify the (multiple) set(s) of *EEWITA* parameters (TL, EL, QL) that satisfy the PSNR and CR requirements. Using computation and communication energy estimation models presented next, the parameter sets are rapidly evaluated, to identify the optimal set of *EEWITA* parameters which minimize energy consumed while satisfying the bandwidth, latency, and image quality constraints.

Since the first and second steps are pre-computed off-line, and only the third step needs to be performed on-line in the mobile appliances or basestation unit, the extra overhead of dynamic selection technique in terms of configuration cost and time is minimal. During wireless communication, the appliance can monitor the image quality, latency, and bandwidth constraints, as well as the battery conditions. If there is a significant change in the conditions or constraints, the third step (table lookup) can be performed in the appliance at run-time, and consequently *EEWITA* adapts to use the new set of parameters.

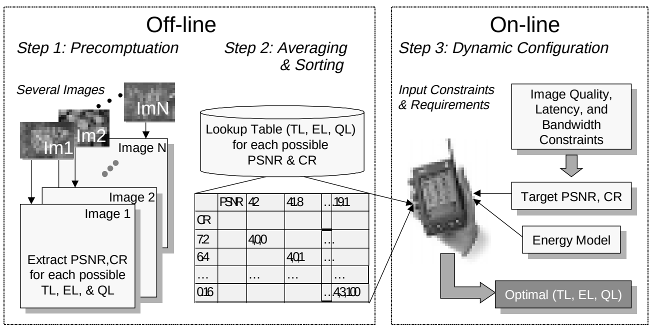


Fig. 10. Dynamic *EEWITA* parameter selection methodology

To enable fast evaluation of the energy consumption for each possible set of *EEWITA* parameters in step 3, we propose an energy estimation model consisting of both computation and communication energy. As shown in Fig. 11, computation energy is computed as a function of the transform and elimination levels chosen, while communication energy is a function of the elimination level, transform level, and quantization level. To characterize the effects of choosing different transform and elimination levels on computation energy, weighting factors *WcompE* and *WdataE* are used, where $WcompE = C_{H*} / C_{AWIC}$ and $WdataE = (C_{READ\_H*} + C_{WRITE\_H*})/(C_{READ\_AWIC} + C_{WRITE\_AWIC})$, where C_{H*}, C_{AWIC}, C_{READ_H*}, C_{WRITE_H*}, C_{READ_AWIC}, C_{WRITE_AWIC} are defined in Sections II-C and III-A. The other constants used for computing energy are dependent on the appliance used (*Ecomp/Pix*, *Edata/Pix*), the image size, and the number of color bands being transmitted (*Band*). *Ecomp/Pix* and *Edata/Pix* represent the computational load and data-access load per pixel of the appliance that the energy model is developed for. Similarly, the constants used for computing the communication energy depend on the communication energy per bit of the appliance (*Ecomm/Bit*), the image size, and number of color bands (*Band*). The compression ratio is estimated using the average across a large number of images as computed in step 2 of our methodology.

Computation Energy = f (Transform_level, Elim_level)
*= (WcompE*Ecomp/Pix+WdataE*Edata/Pix)*ImageSize*Band*

Communication Energy = f (Transfrom_level, Elim_level, Quant_level)
*= (Ecomm/Bit)*CR*ImageSize*Band*

Fig. 11. Proposed energy model for image computation and communication

B. Experimental Results

In this section, we report results of using adaptive *EEWITA* to minimize energy consumption as well as the volume of transmitted bits and air time (service cost) of a service. To determine the energy required to compute and compress an image, we estimated the computational and data-access loads per pixel (*Ecomp/Pix*, *Edata/Pix*) using the SYNOPSYS VHDL RTL power estimation tool [12], and measured the communication energy/bit (*Ecomm/Bit*) using a Palm VII handheld [13] through the Palm.Net wireless network [14]. We use the 512 × 512 size Lena image sample for the experiments reported in this section.

Fig. 12 shows the energy savings available by using the adaptive *EEWITA*, as opposed to the original AWIC image codec which is statically configured for a maximum image quality provision of 40 dB, with parameters used: TL=4, QL=5, EL=0. The top plot shows the energy consumed by the statically configured AWIC codec to deliver images with target PSNR from 20 dB to 40 dB. The energy consumed is constant at 104 J since the parameters are fixed a-priori and cannot be changed. In contrast, using the proposed adaptive *EEWITA* leads to the dynamic parameter selection methodology to select optimal parameters at run-time for a specific image quality requirement (PSNR). As shown by the plot below, application of the adaptive *EEWITA* codec can obtain very significant savings in the energy consumed to compress and deliver images of lower target PSNR. For example, to transmit an image with a PSNR of 25 dB, the total energy savings is over 90 % (around 90 J) compared with the statically configured AWIC.

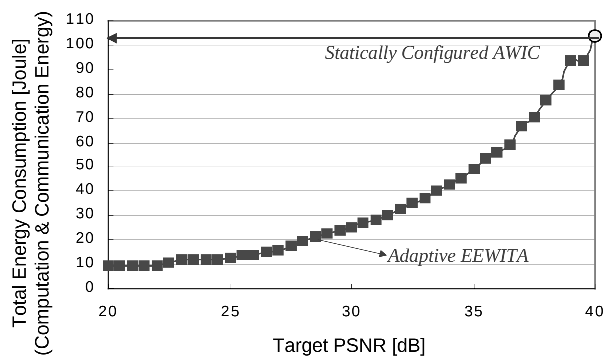


Fig. 12. Energy consumed to transmit 512×512 Lena: Adaptive *EEWITA* vs. statically configured AWIC

Fig. 13 illustrates the impact of our dynamic adaptation technique on energy consumed under different wireless access technologies: Cellular Digital Packet Data (CDPD) [15], IS-95C [16], and Qualcomm's High Data Rate (HDR) [17], with bandwidth availability of 19.2 kbps, 144 kbps, and 2.4 Mbps respectively.

If we assume a strict latency constraint of 1 second, then it will not be possible to use access technologies with a lower bandwidth to transmit high quality images within the latency constraint. For example, transmitting an image of 30 dB using CDPD will require at least 2 seconds, violating the latency constraint. The three horizontal lines in Fig. 13 show the maximum quality of image that can be transmitted by the three access technologies under the 1-second latency constraint, and the energy consumed using the statically configured AWIC codec to provide the maximum image quality possible under that access technology. In contrast, while adaptive *EEWITA* is still constrained by the maximum image quality levels possible under each access technology, it consumes significantly less energy, as shown in Fig. 13. Since the allowable image quality range, and hence the *EEWITA* parameter space, is larger for higher bandwidth access technologies, the energy savings achieved by adaptive *EEWITA* can also be correspondingly higher.

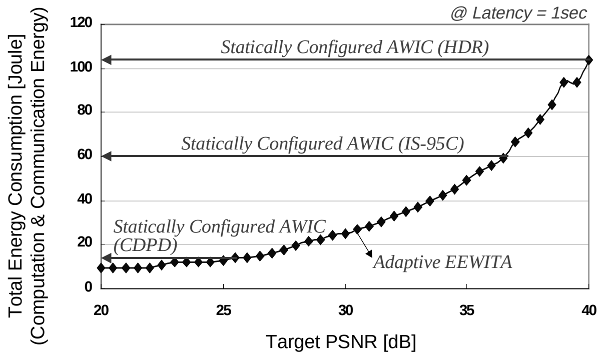


Fig. 13. Impact of adaptive *EEWITA* under different cellular technologies.

Fig. 14 compares the number of image pixels that can be transmitted (y-axis) for a specific energy constraint (x-axis) by using the adaptive *EEWITA*, the statically configured AWIC codec, and without the use of any image compression. The experiments are performed on Lena image, with an image quality constraint of 25 dB. The AWIC codec is configured statically to provide image quality of 40 dB. As can be seen from Fig. 14, use of the adaptive *EEWITA* can transmit on the average 100 times more pixels than the statically configured AWIC codec for a given energy consumption constraint.

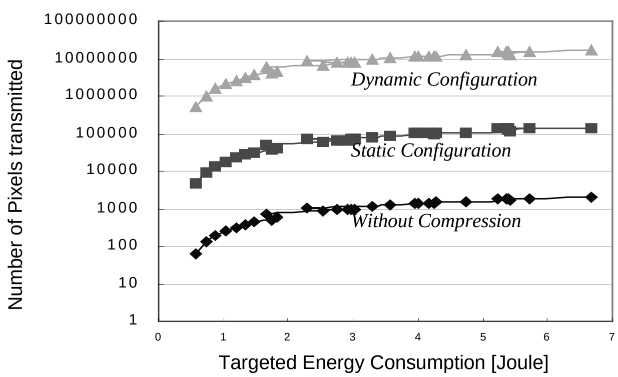


Fig. 14. Impact of adaptive *EEWITA* on pixels transmitted per unit Joule.

Finally, Fig. 15 illustrates the impact of adaptive *EEWITA* on a user's total air time (service cost). By dynamically adjusting *EEWITA* to provide the minimum image quality required (x-axis), significantly less bits of image data need to be transmitted than if the statically configured AWIC codec is used, thereby lowering significantly the air time and cost (y-axis) needed for the service.

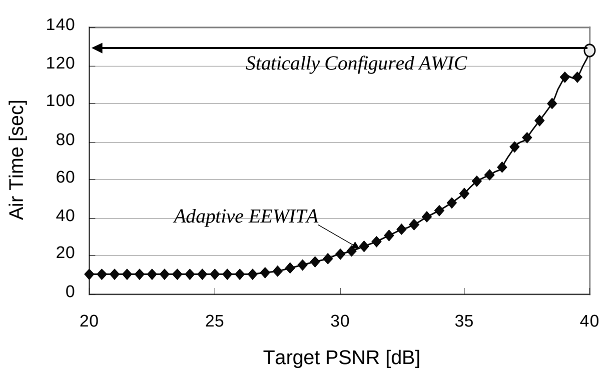


Fig. 15. Effect of adaptive *EEWITA* on user's air time (service cost).

VI. CONCLUSION

Future deployment of cellular multimedia data services will require very large amounts of data to be transmitted, creating tremendously high energy and bandwidth requirements that cannot be fulfilled by limited growth in battery technologies, or the projected growth in available cellular bandwidth. This paper presents a potential solution to the emerging problem, by developing an adaptive, energy efficient image codec. The adaptive *EEWITA* codec enables transmission of image data, an important part of internet and other data applications, with significant savings in the energy consumed and air time (service cost) required, while meeting available bandwidth and data quality constraints. In the future, we will extend our approach to other types of multimedia data like streaming video, as well as address other parameters of wireless data services like transmission latency, transmission robustness, and security.

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